Zero-shot classification of ECG signals using a CLIP-based model

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Abstract

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# Introduction

According to the World Heart Federation (WHF), a leader in global cardiovascular health, among other reports from leading clinicians, researchers and institutions, cardiovascular diseases (CVDs) are a leading cause of mortality worldwide [17; 22; 25; 36]. In the United States, the Center for Disease Control (CDC) estimates that the annual total cost associated with CVD-related treatment and mortality is approximately $219 billion dollars (USD) per year [18; 21]. Given the financial and socioeconomic burdens of CVDs, it is essential that individuals receive timely and accurate medical care for the diagnosis, treatment, and ongoing care of CVDs.

An electrocardiogram (ECG) remains the medical standard and benchmark for the identification and diagnosis of CVDs with more than 300 million ECGs being performed globally [7]. In general, ECGs measure the changes in electrical membrane potential of the heart across different directions of the body and are often referred to as leads with a 12-lead ECG report being the most common type of report [14; 29]. Once an ECG report becomes available, it is ready to be analyzed by a licensed medical professional such as a cardiologist or any other auxiliary medical professional. However, the process of interpreting and analyzing an ECG report is a complex process as it requires a high degree of technical skill and domain knowledge of cardiac anatomy, electrophysiology, pattern recognition, coronary distribution and pathophysiology to perform correctly and accurately [11].

# Related Works

# Materials and Methodology

# Results

# Discussion

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